OPTIMIZATION OF SURFACE ROUGHNESS IN MILLING USING NEURAL NETWORK (NN)

RUZAIMI BIN ZAINON

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SUPERVISOR'S DECLARATION

I hereby declare that I have checked this project and in my opinion, this project is adequate in terms of scope and quality for the award of the degree of Bachelor of Mechanical Engineering with Manufacturing Engineering.

Signature :

Name of Supervisor : Mr Kumaran A/L Kadirgama

Position :Lecturer

Date : 6 December 2010

STUDENT'S DECLARATION

I hereby declare that the work in this thesis my own except for quotations and summaries which have been duly acknowledged. The thesis has not been accepted for any degree and is not concurrently submitted for award of other degree.

Signature :

Name : Ruzaimi Bin Zainon

ID Number : ME07026

Date : 6 December 2010

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ABSTRACT

This thesis discuss the Optimization of surface roughness in milling using Artificial Neural Network (ANN).Response Surface Methodology (RSM) and Neural Network implemented to model the end milling process that are using coated carbide TiN as the cutting tool and aluminium 6061 as material due to predict the resulting of surface roughness. The parameters of the variables are feed, cutting speed and depth of cut while the output is surface roughness. The model is validated through a comparison of the experimental values with their predicted counterparts. A good agreement is found where RSM approaches show 83.64% accuracy which reliable to be use in Ra prediction and state the feed parameter is the most significant parameter followed by depth of cut and cutting speed influence the surface roughness. ANN technique shows 96.68% of accuracy which is feasible and applicable in the prediction value of Ra. The proved technique opens the door for a new, simple and efficient approach that could be applied to the calibration of other empirical models of machining.

ABSTRAK

Kertas kajian ini membincangkan tentang mengoptimum kekasaran permukaan dalam proses pengilingan manggunakan pendekatan dari ANN. Pendekatan Kaedah tindak balas permukaan (RSM) dan ANN digunakan dalam menganalisis nilai kekasaran permukaan aluminium 6061 iaitu bahan eksperimen yang di potong oleh karbida yang diselaputi titanium nitrat (TiN). Data masuk adalah kelajuan memotong,kedalaman memotong dan kadar pergerakan pemotong dan data yang dinilai adalah kekasaran permukaannya. Nilai ramalan kekasaran permukaan dianalisis oleh kaedah RSM dan ANN. Kemudian nilai analisis terbabit akan dibandingkan dengan nilai eksperimen. Pendekatan RSM menunjukan ketepatan ramalan sebanyak 83.64%yang boleh diguna pakai dalam ramalan kekasaran permukaan dan kadar pergerakan pemotong memainkan peranan yang penting dalam mempengaruhi nilai kekasaran permukaan di ikuti oleh kedalaman dan kelajuan pemotongan. Manakala pendekatan ANN menunjukkan 96.68%ketepatan dalam menganalisis nilai kekasaran permukaan.Teknik dan pendekatan ini terbukti membuka pintu untuk pendekatan baru, mudah dan efisien yang boleh diterapkan dalam mendapatkan nilai kekasaran permukaan yang diperlukan.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

α	Alpha
μm	Micrometer
R^2	Coefficient of Determination

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ACO	Ant Colony Optimization
Adj	Adjusted
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
CNC	Computer Numerical Control
CS	Cutting Speed
DF	Degree of Freedom
DOE	Design of experiment
DOC	Depth of Cut
Exp	Exponential
MSE	Mean Square Error
PSO	Particle Swarm Optimization
Ra	Average Surface Roughness
RPM	Revolution per Minute
RSM	Response Surface Methodology
SS	Sum of Square
TiN	Titanium Nitrate
Vs	Versus

CHAPTER 1

INTRODUCTION

1.1 PROJECT BACKGROUND

This thesis involves an experimental and theoretical to predict Optimization of Surface Roughness in Milling using Neural Network (NN). Surface roughness is very important due to it is one of the most specified customer requirements and the major indicator of surface quality on machined parts is surface roughness. The surface roughness is mainly a result of various controllable or uncontrollable process parameters and it is harder to attain and track than physical dimensions are.

Neural Network (NN) is implemented to model the end milling process and predict the resulting surface roughness. Data is collected from CNC cutting experiments using DOE approach in order to get the design table and Response Surface Methodology (RSM) as the technique to predict and analyze the result. The data is used for model calibration and validation.

The inputs to the model consist of feed rate, cutting speed and depth of cut while the output from the model is surface roughness. The model is validated through a comparison of the experimental values with their predicted counterparts. A good agreement is found. The proved technique opens the door for a new, simple and efficient approach that could be applied to the calibration of other empirical models of machining.

1.2 OBJECTIVE OF STUDIES

The objectives of the studies are shown below;

1. To predict the parameter that contributes to the optimum surface roughness value.
2. To study the relationship between the parameter that leading to the optimum surface roughness.

1.3 PROJECT SCOPE

This project considers on investigating ofOptimization of Surface Roughness in Milling by using Neural Network (NN).It will start with literature review and understands the statement of problem. In addition, the effect of major parameters influencing the surface roughness due to machining also will be discussed. In general the experiment will be doing by:

i. The material use is Aluminium 6061.
ii. The cutting tool is coated carbide TiN.
iii. The depth of cut range is 1 mm to 2 mm.
iv. The cutting speed range is 100mm/min to 180 mm/min.
v. The feed range is 0.1 mm/tooth to 0.2 mm/tooth.

1.4 PROBLEM STATEMENT

Establishment of efficient machining parameters confronted manufacturing industries for nearly a century, and is still the subject of many studies. Optimum machining parameters are of great concern in manufacturing environments, where economics of machining operation plays a key role in competitiveness in the market. Besides that surface roughness value were optimize in milling using Neural Network (NN)method. This prediction is depending on other parameter which is depth of cut, cutting speed and feed rate.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

The surface parameter used to evaluate surface roughness in this study is the roughness average (*Ra*).The roughness average is the area between the roughness profile and its central line, or the integral of the absolute value of the roughness profile height over the evaluation length. There are a great number of factors influencing the surface roughness and Figure 2.1 shows all influential factors on machined surface roughness (Benardo and Vosnaikos, 2003).

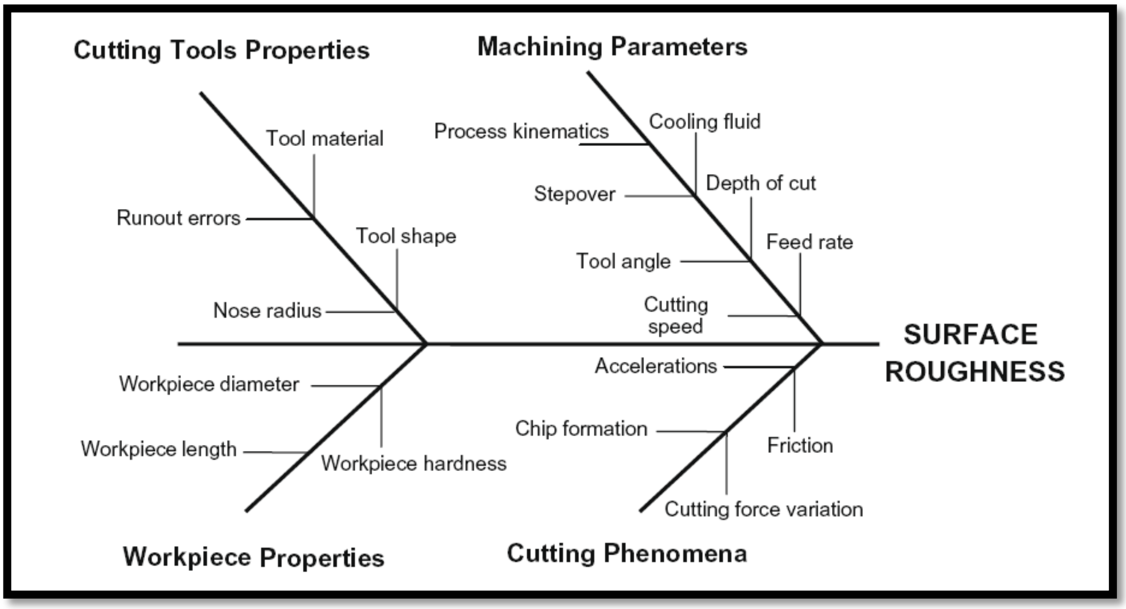

Figure 2.1: Parameter that affects surface roughness

(Source: Benardo and Vosnaikos ,2003)

In order to develop a surface prediction, literature review of the surface texture, surface finish parameters, and multiple regression analysis have been carried out and summarized as follows:

2.1.1 Surface Texture

The term surface finish and surface roughness are used vary widely in industry and are generally used to quantify the smoothness of a surface finish. In 1947, the American Standard B46.1-1947, "Surface Texture", defined many of the concepts of surface metrology and terminology which overshadowed previous standards. A few concepts are discussed and shown as follows (Dr.Mike *et al*,. 1999):

(i) Surface texture: Surface texture is the pattern of the surface which deviates from a nominal surface. The deviations may be repetitive or random and may result from roughness, waviness, lay, and flaws.

(ii) Real surface: The real surface of an object is the peripheral skin which separates it from the surrounding medium. This surface invariably assimilates structural deviations which are classified as form errors, waviness, and surface roughness.

(iii) Roughness: Roughness consists of the finer irregularities of the surface texture, usually including those irregularities that result from the inherent action of the production process. Profiles of roughness and waviness are shown in Figure 2.2.

(iv) Roughness width: Roughness width is the distance parallel to the nominal surface between successive peaks or ridges which constitute the predominant pattern of the roughness.

(v) Roughness width cutoff: Roughness width cutoff is included in the measurement of average roughness height which denotes the greatest spacing of repetitive surface irregularities. It is rated in thousandths of an inch. Standard tables list roughness width cutoff values of 0.003, 0.10, 0.030, 0.100, 0.300 and 1.000 inches. If no value is specified, a rating of 0.030" is assumed.

(vi) Waviness: Waviness should include all irregularities whose spacing is greater than the roughness sampling length and less than the waviness sampling length.

(vii) Waviness height: Waviness height is the peak-to-valley distance which is rated in inches.

(viii) Waviness width: Waviness width is the spacing of successive wave peaks or successive wave valleys which is rated in inches.

(ix) Lay: Lay is the direction of the predominant surface pattern, normally determined by the production method.

(x) Flaws: Flaws are unintentional, unexpected, and unwanted interruptions in the topography typical of a part surface.

(xi) Roughness sampling length: The roughness sampling length is the sampling length within which the roughness average is determined. This length is chosen, or specified, to separate the profile irregularities which are designated as roughness from those irregularities designated as waviness.

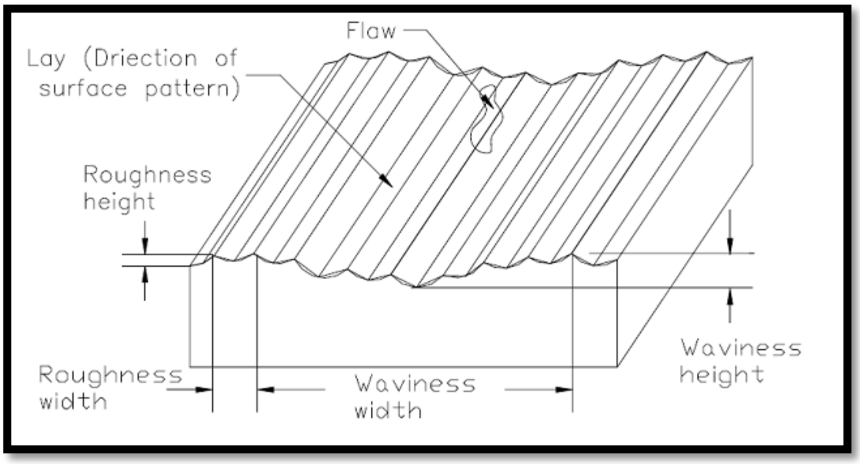

Figure 2.2: Roughness and Waviness Profile

(Source: Dr.Mike et al,. 1999)

2.1.2 Surface Finish Parameters

Surface finish could be specified in many different parameters. Due to the need for different parameters in a wide variety of machining operations, a large number of newly developed surface roughness parameters were developed. Some of the popular parameters of surface finish specification are described as follows:

i. Roughness average (Ra): This parameter is also known as the arithmetic mean roughness value, AA (arithmetic average) or CLA (center line average). Ra is universally recognized and the most used international parameter of roughness. Therefore,

$$R_a = \frac{1}{L}\int_0^L \left|Y(x)\right| dx \qquad (2.1)$$

Where; R_a = the arithmetic average deviation from the mean line
L = the sampling length
Y = the ordinate of the profile curve

It is the arithmetic mean of the departure of the roughness profile from the mean line. An example of the surface profile is shown in Figure 2.2.

ii. Root-mean-square (rms) roughness (Rq): This is the root-mean-square parameter corresponding to Ra:

$$R_q = \sqrt{\frac{1}{L}\int_0^L Y(x)^2 dx} \qquad (2.1)$$

iii. Maximum peak-to-valley roughness height (Ry or Rmax): This is the distance between two lines parallel to the mean line that contacts the extreme upper and lower points on the profile within the roughness sampling length. Since Ra and Rq are the most widely used surface parameters in industry, Ra was selected to express the surface roughness in this study.

2.1.3 Multiple Regression Analysis

Since multiple regression is used to determine the correlation between a criterion variable and a combination of predictor variables, the statistical multiple regression method is applied. It can be used to analyze data from any of the major quantitative research designs such as causal-comparative, correctional, and experimental. This method is also able to handle interval, ordinal, or categorical data and provide estimates both of the magnitude and statistical significance of the relationships between variables (Gall and Borg, 1996). Therefore, multiple regression analysis will be useful to predict the criterion variable finish surface roughness via predictor variables such as feed rate, cutting speed, or depth of cut.

Multiple Regression Prediction Model

The proposed multiple regression models are a three-way interaction equation:

$$\boldsymbol{Y_i = \alpha_i + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{1i} X_{2i} + \beta_5 X_{1i} X_{3i} + \beta_6 X_{2i} X_{3i} + \beta_7 X_{1i} X_{2i} X_{3i}} \quad (2.3)$$

Where;

$\boldsymbol{Y_i}$: Surface roughness Ra (micro mm)

$\boldsymbol{X_{1i}}$: Spindle speed (revolutions per minute)

$\boldsymbol{X_{2i}}$: Feed rate (mm per minute)

$\boldsymbol{X_{3i}}$: Depth of cut (mm)

In this model, the criterion variable is the surface roughness (Ra) and the predictor variables are spindle speed, feed rate, and depth of cut. Because these variables are controllable machining parameters, they can be used to predict the surface roughness in milling which will then enhance product quality.

2.2 NEURAL NETWORKS (NN)

An Artificial Neural Network (ANN) is a system based on the operation of biological neural networks, in other words, is an emulation of biological neural system and information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. There are certain tasks that a program made for a common microprocessor is unable to perform even so a software implementation of a neural network can be made with their advantages and disadvantages. Figure 2.3 shown an example the structure of the ANN that consists of input, output and hidden layer.

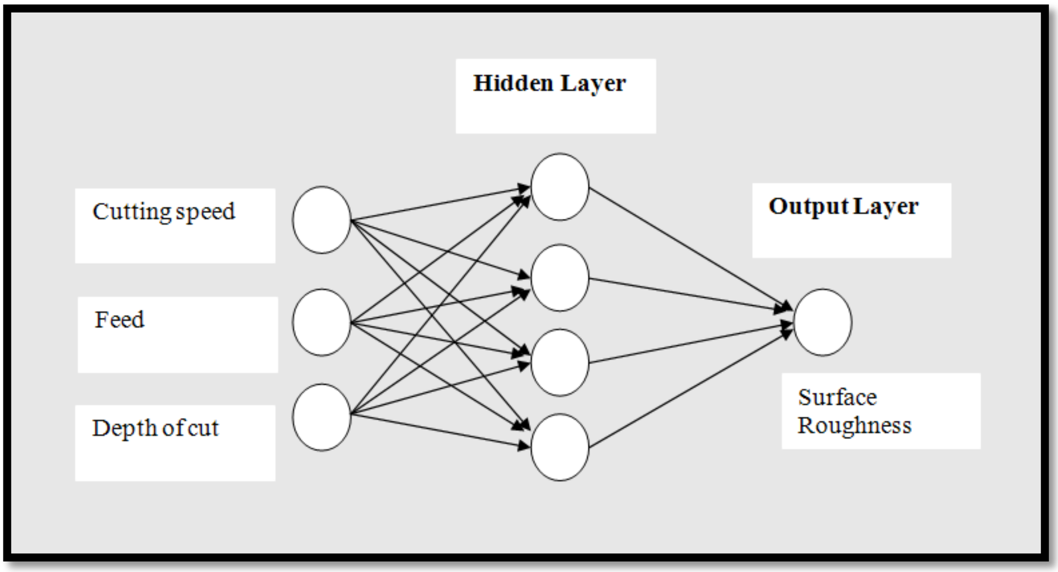

Figure 2.3: ANN structure

ANN has their advantages and disadvantages. A neural network can perform tasks that a linear program cannot. When an element of the neural network fails, it can continue without any problem by their parallel nature. Besides that a neural network learns and does not need to be reprogrammed. It can be implemented in any application without any problem.

The disadvantages of this method are the neural network needs training to operate. The architecture of a neural network is different from the architecture of microprocessors therefore needs to be emulated. And last but not less it requires high processing time for large neural networks.

2.3 MILLING PROCESS

2.3.1 Introduction

The requirement of industry regarding manufacturing of a component is very complex. This may be because of complexity of the job profile or may be due to requirements of higher dimensional accuracy with high surface finish. Efforts are being continuously made to overcome all of these problems. The basic principle of metal removal in the conventional methods of machining involves the use of tool, which is harder than the work piece and is subjected to wear.

High accuracy CNC milling machines are required in many manufactures because the demand of precision components and consistency of quality are growing. The most important factor of the precision components is the accuracy of machine tools. Generally position errors are originated from geometric, cutting force, dynamic loading, and so on. Various sources of geometric errors that were usually encountered on machine tools and the methods of error compensation employed in machines.

2.3.2 CNC Milling Machine

Computer Numerical Control (CNC) Milling is the most common form of CNC. CNC mills can perform the functions of drilling and often turning. CNC Mills are classified according to the number of *axes* that they possess. Axes are labeled as x and y for horizontal movement, and z for vertical movement, as shown in this view of a manual mill table.

CNC milling machines are traditionally programmed using a set of commands known as *G-codes*. G-codes represent specific CNC functions in alphanumeric format. In modern CNC systems, end-to-end component design is highly automated using CAD/CAM programs. The programs produce a computer file that is interpreted to extract the commands needed to operate a particular machine, and then loaded into the CNC machines for production.

Since any particular component might require the use of a number of different tools, drills, saws, and so on, modern machines often combine multiple tools into a single "cell". In other cases, a number of different machines are used with an external controller and human or robotic operators that move the component from machine to machine. In either case, the complex series of steps needed to produce any part is highly automated and produces a part that closely matches the original CAD design. USB flash drives and local area networking have replaced the tapes to some degree, especially in larger environments that are highly integrated.

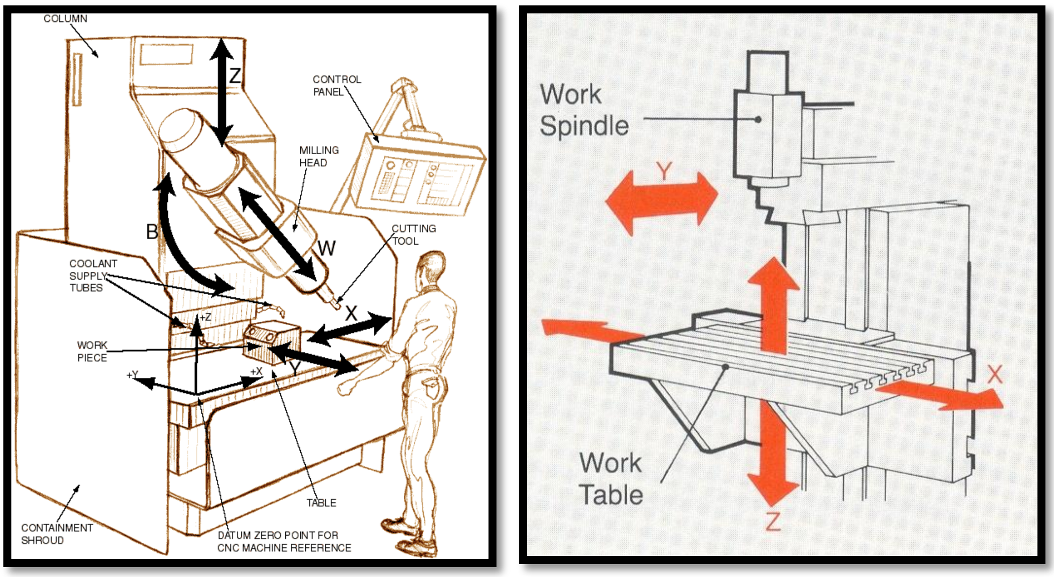

Figure 2.4: CNC Milling Machine

(Source: http://www.cncmillinglathe.com)